Textural segmentation of high-resolution sidescan sonar images.

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Abstract

The collection of high-frequency (455 kHz) sidescan data from tactical sonars used in mine countermeasures (MCM) is typically for the purpose of object and clutter identification. The large amounts of high-frequency high-resolution sidescan imagery are also a potential source of data for environmental battlespace characterization. The high resolution of the 455 kHz sonar imagery also provides much information about the surficial bottom sediments, however their acoustic scattering properties are not well understood at high frequencies. Textural characteristics of the high-resolution imagery are therefore used to represent the different scattering properties of various sediment types. The fusion of this data with collateral seafloor information from other tactical sensors or databases, can be used for classification. The operational goal is to use the sidescan-derived features with a vertical-incidence sediment classifier to infer sediment properties at angles off of vertical incidence that can then be used in mine burial prediction models, acoustic performance models, and survey planning.

1 Introduction

Sediment acoustic-scattering properties at high frequencies is an area of much interest and active research [1],[2],[3],[4],[5],[6]. For tactical purposes, the probability of detection of objects on the seafloor is highly dependent on background scattering properties, particularly in cluttered environments. The high-resolution, high-frequency sidescan sonars are very well suited to the task of object detection. The high-resolution imagery of the acoustic response of the seafloor also provides a large amount of *data of opportunity* for mapping the seafloor. However, since the high-frequency acoustic sediment physics are not well understood, a classification approach based on textural segmentation is used. The fusion of this data with collateral seafloor information from vertical incidence, lower frequency multibeam, or other tactical sensors or databases, can be used to classify the low grazing angle data. The objective is to use the acoustic impedance information to label the segmented image data.

The Klein 5500 sidescan sonar operates at 455 kHz and uses a dynamically-focused aperture to produce five parallel beams per ping. The beams have a constant resolution of either 10 or 20 cm along track, and an across-track resolution of 3.75 cm. The Klein 5500 imagery used in this study was collected by the U.S. Naval Oceanographic Office off the coasts of Corpus Christi, TX and Panama City, FL. Impedance data was derived from the UQN-4 vertical incidence sonar, the standard fathometer for all U.S. Navy ships. The impedance data were collected at different times from the sidescan data.

The segmentation of the data using several texture algorithms is discussed in this paper, and some results for the Panama City data set are presented. Some preliminary results are presented on the fusion of the impedance data with texture.

2 Texture analysis

Texture measures the patterns of acoustic intensity fluctuations,that can be used to discriminate between sediments. Textural features are derived from grey-level cooccurrence matrices (GLCM) [7], frequency-domain measures, higher-order moments, and fractal dimensions [8],[9].

The GLCM-derived features are entropy, homogeneity, contrast, and correlation. The texture features are constructed from the slant-range corrected data for several adjacent pixel orientations, $\theta = 0°, 45°, 90°,$and $135°$ (in Cartesian space) and inter-pixel distances, $d = 1, 2$. The cooccurrence probabil-

REPORT DOCUMENTATION PAGE	*Form Approved* *OMB No. 0704-0188*

1. REPORT DATE *(DD-MM-YYYY)*	2. REPORT TYPE	3. DATES COVERED *(From - To)*
May 1995	Proceeding	

4. TITLE AND SUBTITLE
Textural segmentation of high-resolution sidescan sonar images.

5a. CONTRACT NUMBER

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER
62435N

6. AUTHOR(S)
Kalcic, Maria, Bibee, Dale,

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Naval Research Laboratory
Seafloor Sciences Branch
Stennis Space Center, MS 39529

8. PERFORMING ORGANIZATION REPORT NUMBER
NRL/PP/7430-04-2

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
Office of Naval Research
800 North Quincy Street
Arlington VA 22217-5000

10. SPONSOR/MONITOR'S ACRONYM(S)
ONR

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; distribution is unlimited

13. SUPPLEMENTARY NOTES
Sixth International Symposium on Technology and the Mine Problem, Monterey, CA, 9-13 May 2004, CD

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15. SUBJECT TERMS
sidescan sonar, mine countermeasures,

16. SECURITY CLASSIFICATION OF: a. REPORT	b. ABSTRACT	c. THIS PAGE	17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON	19b. TELEPHONE NUMBER *(Include area code)*
UL	UL	UL	UL	6	Leonard Dale Bibee	228-688-5459

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ities are averaged over the four directions to stabilize the variance due to the high rate of towfish motion, and changes in track heading as well. These averaged features are considered rotationally invariant.

The higher-order central moments of the data are used primarily to incorporate the relative mean backscatter. The mean, variance, skewness and kurtosis are computed for each block of pixels used in the analysis. A mean backscatter parameter is derived from the data by removing all angle-varying or range-dependent gains. The resulting parameter is adjusted by an arbitrary constant that represents the overall system gain, thus the mean backscatter is relative. The inclusion of the first central moment, or mean, as a feature in the classifier makes the resulting segmentation a function of mean backscatter as well as texture.

The fractal features are constructed for the horizontal and vertical directions following Linnett [8],. This approach derives the fractal dimension based on the brightest reflectors and lowest reflectors, producing an upper and lower fractal surface respectively, at spatial resolutions $\tau = 1, 2, and\ 4$.

Texture features can be described by the spatial distribution of the two-dimensional Fourier transform, and the speed with which the FFT can be computed, makes it an appealing choice for near real time applications. The 2-D spatial spectra for an area of uniform texture contain information on the direction, magnitude and wavelength of spatial patterns in that area. Sand ridges are a good example of a directional periodic texture. If the sand waves consisted of a single wavelength, with crest and trough of equal shape and size, then the spatial spectrum would be an impulse at a single point. As the wavelength varies, the spectrum broadens in the wave direction. If the area is homogeneous with random scatterers then spectrum will be randomly distributed.

To exploit the frequency coherence seen in sand ripple patterns, a measure of the squared coherence between the horizontal and vertical frequency components is a useful metric. The 2D-FFT is performed over the image using smaller overlapping windows. The data are tapered with a Gaussian window with large σ to preserve spectral resolution. The spectral texture features are derived by first identifying areas of higher energy in the spectrum. The expected energy for a 2-D white noise field is used. The spectral energy of the image is compared to the expected energy. A binary image is created by setting a bit if the energy exceeds a predetermined threshold. The expected noise field can be modelled in any number of ways, to satisfy assumptions about the noise statistics.

A set of $\{x, y\}$ coordinates is generated for each bit set in each block of the binary image. By computing a least squares fit between the $\{x, y\}$ coordinates , the slope, β, intercept, α, and goodness of fit, R^2 are derived. . The statistics indicate whether there is a strong linear trend (high R^2) or random scatter, (very low R^2). The slope, offset and R^2 values are saved as features for each block of the image, although the slope and offset are not used for texture parameters.

The set of features is reduced to a few parameters that correlate with some known physical property. Presently, principal components are used to reduce the set of features for classification. A more optimal approach is to construct features based on the best separation of seafloor bottom types of interest, provided there is sufficient ground truth. Since the data are not segmented into classes to begin with, and there is little or no ground truth to base the classification on, we have to derive an estimate of the statistics from the data. A K-means clustering algorithm is used which reassigns pixels to different clusters while trying to minimize the within-cluster variance. The algorithm proceeds until the number of clusters reaches a predefined threshold. The clusters each represent a bottom type, which is unknown, i.e. unsupervised classification. Classification is performed using a Bayesian maximum likelihood test [10]. The final classification produces a segmentation of the image based on the individual cluster statistics. The fusion of the texture data with the impedance data or some ground truth will be used to identify the classes.

3 Segmentation approach

All quantifiable range-dependent effects are removed from the sidescan data to make the images represent relative mean backscatter. The backscatter analysis presumes a flat bottom and uses the sonar equation to correct for systematic and random processes that affect the overall system gain. The system is solved for reverberation using

$$RL = SL - 2TL + S_b + 10 \log A$$

where RL is the area reverberation for a unit area at range r,and S_b, is the scattering strength [11]. The scattering strength is expressed using Lambert's Law, which gives the scattering strength as a function of grazing angle, θ as

$$S_b = 10 \log_{10} \mu + 10 \log_{10} \sin^2 \theta$$

where $10\log_{10}\mu$ is a constant approximately equal to the average scattering strength, independent of grazing angle.

The quantity $10\log_{10}\mu$ is estimated from the data and the result is quantized to 8 bits for image processing.. After removing the angular dependence in the data and converting it to 10 log μ,the resulting image is approximately Gaussian, whereas the original image was closer to a Rayleigh distribution. The more normal distribution makes many of statistical algorithms more robust.

The relative mean backscatter, $10\log_{10}\mu$,is compared between several areas off Corpus Christi known to be predominantly sand and mud. The mean backscatter curves for the sand and mud areas, i.e. ECHO 2 and CHARLIE 2/DELTA/ECHO 3, respectively are shown in figure 1. Each line represents an average $10\log_{10}\mu$ over a separate survey track and is plotted with time for comparison. The plots show a clear separation between the mud and sand profiles, with 3-10 dB of separation. This information is useful for discriminating between the two bottom types even though a physical model is not available.

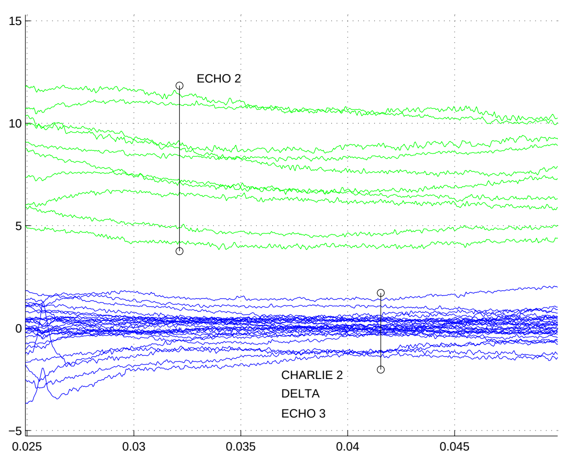

Figure 1: Relative mean backscatter (dB) vs. time (sec). Upper set of lines are for ECHO 2, which is mostly sand; the lower set are for ECHO 3, DELTA, and CHARLIE 2, which are mostly mud.

The 10 log μ values are corrected for slant range and quantized to 8-bits for texture processing. The GLCM, moments, spectral, gradient, and fractal features are computed and reduced to a set of principal components. The mean backscatter is included as a feature in the first moment.

An example of the frequency domain features is shown for the image in figure 2. The seafloor imaged withe the Klein 5500 near Panama City, FL is composed of sand ridges with an area of shell, sand, and coral debris at the bottom of the image. The 2D-FFT is applied to each block within the image, and results are shown in figure 3. The vertical and horizontal components of the sand ridges are correlated, producing the linear pattern, and thus a high r^2 value when a linear fit is applied. The results are shown in figure 4. The image on the left shows the r^2 values, and the right-hand image shows the slope of the line. The image of the r^2 values shows values greater than 0.65 for the sand ridges, and much lower values, less than 0.20, for the sand, shell and coral debris. The slope image shows the direction of the sand waves to be 0.5 to 1.0, or just near 45°.relative to the horizontal axis. The slope angle, corrected for ship's heading, gives the direction of the wave pattern.

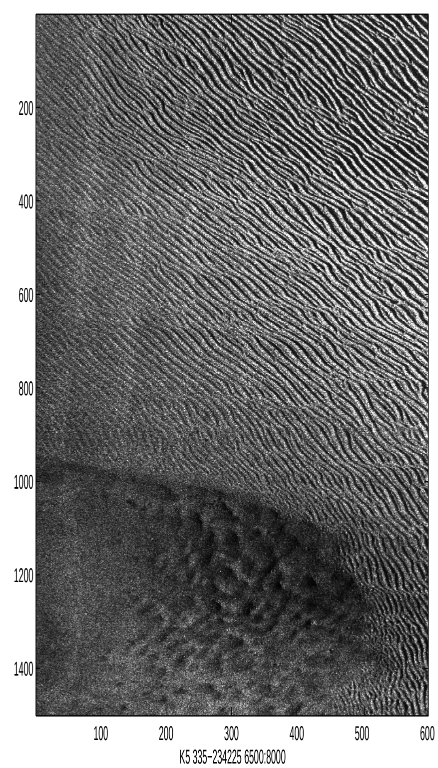

Figure 2: Klein-5000 sidescan image from Panama City Survey Area BRAVO (K5-335-234225) shows sand ridges at top, nadir at left.

Texture features were computed for the two bottom types, sand ridges and an area of shells, sand and coral debris, seen in figure 2. In figure 5 a scatter plot is shown of contrast vs. entropy for all the points in each bottom type. The plot shows there

is separation as indicated by the line, although some overlap is present. The scatter plot of three texture features, entropy, contrast, and r^2, for each bottom type is shown in figure 6. The separation between these two bottom types based on the three features gives a better separation, as expected. A test statistic can be constructed as a linear combination of the three or more texture features and used to classify the pixels into one of the two classes. Principal components are used to form linear combinations of the 22 texture measures to two or three uncorrelated features, which are then used in classification.

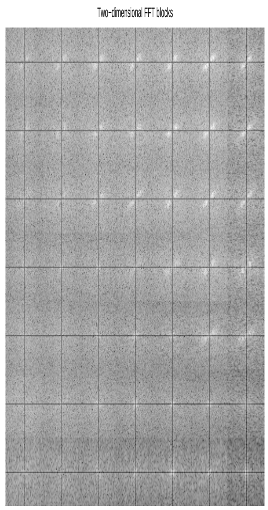

Figure 3: Results of 2-D (64x64) FFT over adjacent image blocks. Linear features indicate presence and orientation of sand ridges.

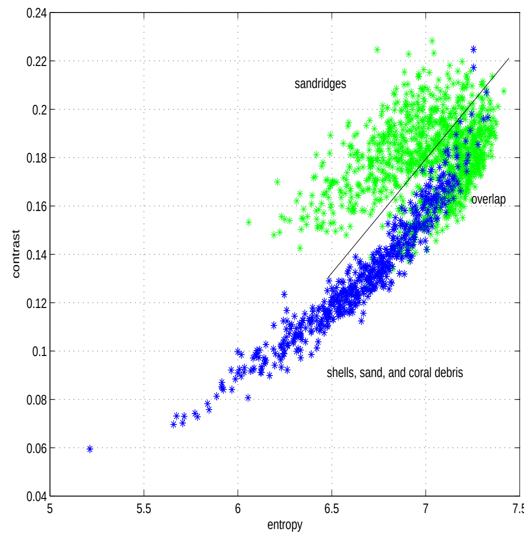

Figure 5: Scatter plot of texture features entropy and contrast for areas of sand ridges and and sand/shells/coral debris. Line indicates where a discriminant function might be used to classify based on these two features alone. Overlap indicates existence texturally similar subareas.

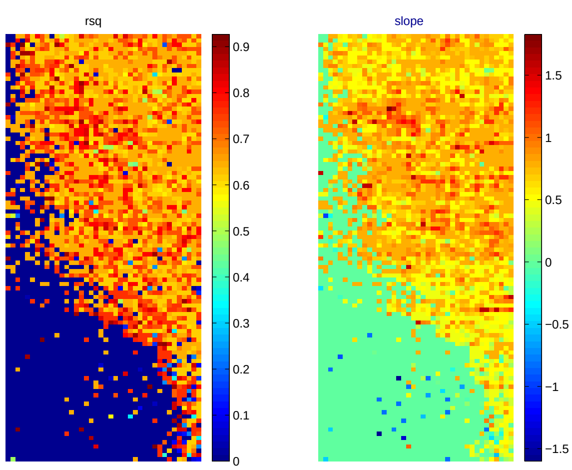

Figure 4: Example of spectral parameters: (a) directional strength R^2 ; (b) linear slope

In practice, the bottom types are not known *a priori* so a statistical test between blocks of data is used to build homogeneous statistical classes. These statistics are used as a basis for segmentation. Segmentation is performed using either a maximum likelihood statistic or a Poisson-scattering based rule [12]. The classification result for the image in figure 2 using the maximum likelihood method with the first two principal components is shown in figure 7. Results show that near-nadir results are not as good for the sand ridge discrimination because of the low contrast that results from the higher grazing angle. However, some features are more robust to contrast than others, suggesting that a different feature set should be used. Also, the use of training data would be useful for op-

timum feature selection. For most of the off-nadir data, these results and others [13], [6], [12],[1],[14], show that several seafloor bottom types can be distinguished based on textural characteristics.

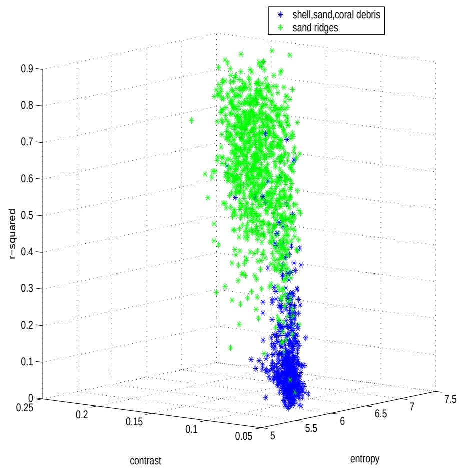

Figure 6: Scatter plot of texture features (entropy, contrast, r^2) from images of sand ridges and shell/sand/coral debris.

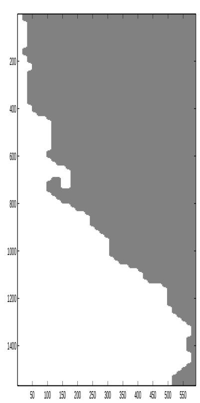

Figure 7: Texture segmentation of Panama City sidescan image shown in Figure 1. Gray indicates sand ridges, white indicates shell, sand and coral debris.

Figure 8 shows an overlay of impedance values to a texture classification of some of the Panama City data. There are two texture classes represented as gray and white. While the gray areas correlate with higher impedances ($\geq$ 3.0), the white areas correlate with lower impedances($<$ 3.0) in some areas, and higher impedances in other areas. The gray area with high impedances is indicative of coarse sand in this area. The white area with lower impedance correlates with finer sand, while the white area (upper left) with higher impedances are likely areas of coarse sand, with some coral debris and perhaps gravel. There is also the possibility that the texture is identifying a thin layer of surficial sediments over a layer with different sediment properties that can be detected by the low-frequency sonar, but not the high-frequency sidescan.

4 Conclusions

Segmentation of sidescan data is useful for seafloor classification for several reasons. The sidescan data are used by the Naval Oceanographic Office to update their seafloor bottom-type databases, a manual task best performed by experienced seafloor analysts. The use of the texture-segmentation results in a data fusion approach to seafloor classification using collateral data, can be used to infer sediment properties useful for tactical purposes. Presently the Klein sidescan data are being combined with the UQN-4 vertical incidence data, from which acoustic impedances are estimated. The texture-segmented data will be classified with acoustic impedances from overlying tracks of UQN-4 data, providing wider bottom coverage.

Several textural features applied to high-resolution high-frequency sidescan data have been presented. The use of a combination of features has shown that good discrimination is possible for areas of well defined sand ridges and other textures. Segmentation results need to be evaluated with the impedance data. In cases where a texture shows different impedances, direct bottom sampling would be useful for evaluating discrepancies.

Acknowledgement *This work was funded under Program Element 62435N, Battlespace Environments, Office of Naval Research.*

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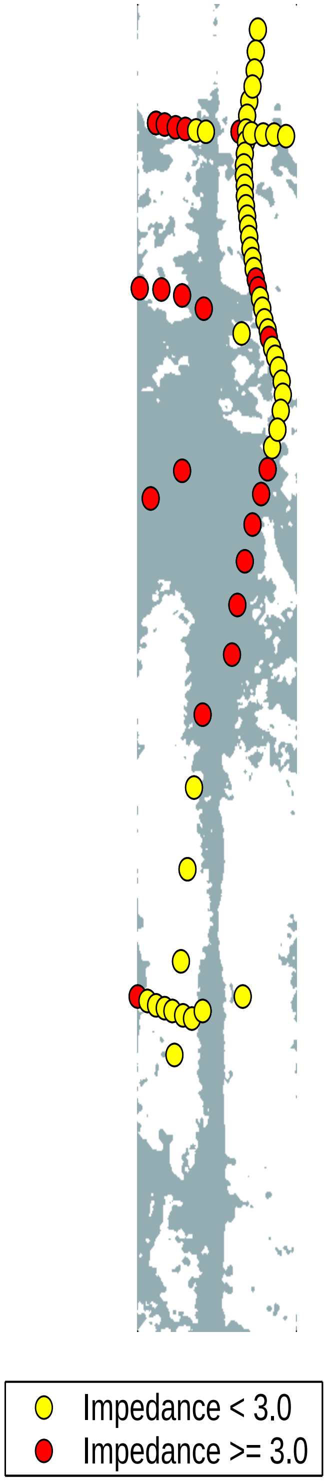

Figure 8: Texture-segmented Klein 5500 image overlaid with acoustic impedances. Preliminary result shows impedance values in range 3-5 corresponding to one class (white), and the lower impedance values in the range 1-3 corresponding to another class (dark gray) .

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